The Inductive Monitoring System (IMS)

Learns how the system typically behaves and tells you if it is behaving differently now

The Inductive Monitoring System (IMS) combines features of model based reasoning and data clustering to build system health monitoring knowledge bases from archived or simulated system sensor data.

Background

We developed the Inductive Monitoring System (IMS) software to provide a technique to automatically produce health monitoring knowledge bases for systems that are either difficult to model (simulate) with a computer or which require computer models that are too complex to use for real time monitoring. IMS uses data sets collected either directly from the system or from simulations to build a knowledge base that can be used to detect anomalous behavior in the system. Machine learning and data mining techniques are used to characterize typical system behavior by extracting general classes of data from archived data sets. IMS is able to monitor the system by comparing real time operational data with these classes.

Research Overview

Model based reasoning is a powerful method for performing system monitoring and diagnosis. Typical model based reasoning techniques compare a system model or simulation with system sensor data to detect deviations between values predicted by the model and those produced by the actual system. However, building models for model based reasoning is often a difficult and time consuming process. IMS provides a method that can monitor the health of a system with nearly the same fidelity as the model based method, but without the need to manually build a model. IMS automatically defines groups of consistent system parameter data by examining and generalizing from examples of system data. With a sufficiently broad data set, the knowledge base produced by IMS should contain most or all of the consistent parameter value combinations necessary to effectively characterize and monitor system operation. After learning how the system behaves when operating correctly, IMS can identify off nominal behavior and send appropriate alert messages to system operators.

Figure 1: The Inductive Monitoring System (IMS)

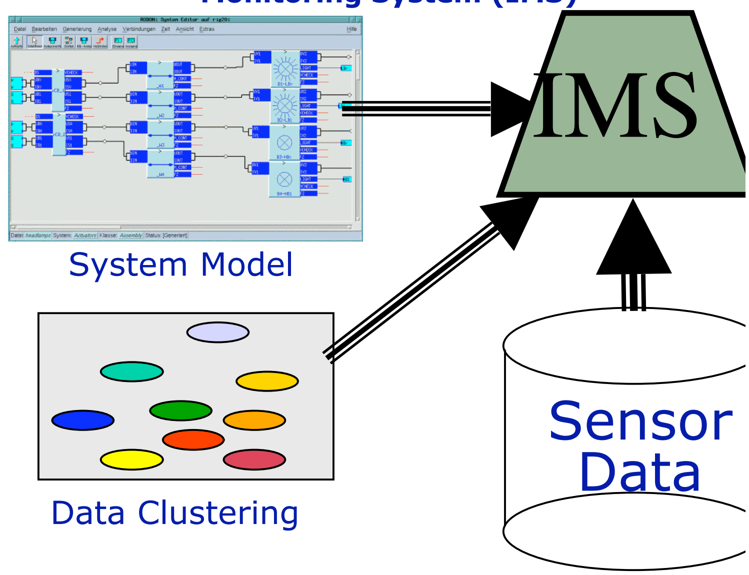
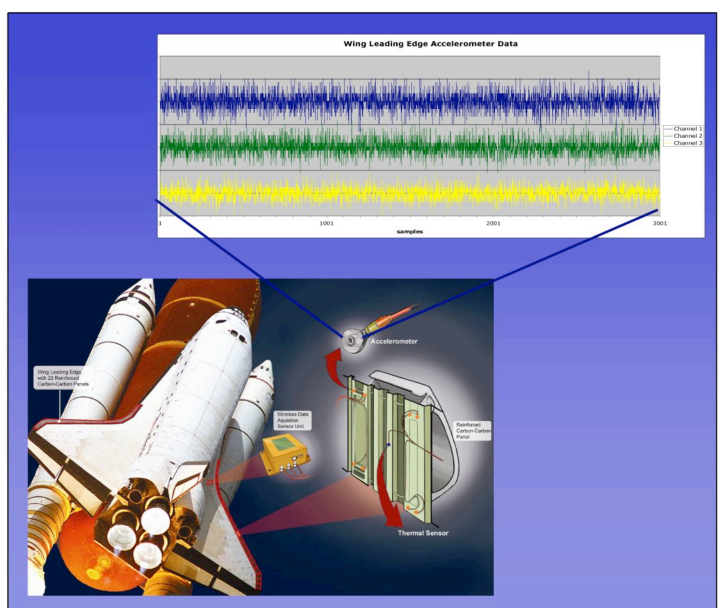


Figure 2:IMS analysis of data collected from a mission



How the Inductive Monitoring System (IMS) works

Learning and Modeling

IMS learns nominal system behavior from archived or simulated system data, automatically builds a "model" of nominal operations, and stores it in a knowledge base. Machine learning and data mining techniques are used to characterize typical system behavior by extracting general classes of nominal data from archived data sets. In particular, IMS uses clustering to group sets of consistent parameter values found in the training data. Clustering is the unsupervised assignment of elements of a given set to groups or clusters of similar points.

Monitoring

IMS real-time monitoring display informs users of degree of deviation from nominal performance. Trend analysis can detect conditions that may indicate an incipient failure or required system maintenance. The fastest IMS monitoring schemes require that the input data vectors be contained inside at least one of the knowledge base clusters This eliminates the need to perform distance calculations. A more informative monitoring technique will locate the cluster in the monitoring knowledge base that is closest to the input vector, and report the distance of that vector from the cluster. This will give the operator an idea of how far the system behavior is deviating from nominal operation as represented by the training data. IMS applications to date have successfully monitored 1 KHz data rates without distance calculations and 50 Hz data rates with distance calculations on computers running with clock speeds under 1 GHz.

An IMS Application Example

The IMS methodology is domain independent and can be used in a variety of system monitoring situations including aerospace, transportation, manufacturing, power generation and transmission, medical, or process monitoring applications. Of particular interest to NASA is the application to Integrated Vehicle Health Management (IVHM), either on board a vehicle or in a mission control room. To demonstrate the utility of IMS in a mission control setting, we recently built an IMS knowledge base to monitor temperature sensors in the wings of a Space Shuttle Orbiter, and used that knowledge base to analyze archived telemetry data collected from the ill-fated STS-107 Columbia Space Shuttle mission. This flight came to a disastrous end when the Columbia orbiter was destroyed during reentry, claiming the lives of all seven crew members. The ultimate cause of the accident was determined to be a breach in the Thermal Protection System on the leading edge of the left wing, caused by a piece of insulating foam that struck the wing approximately 82 seconds after launch. The first indication of the damage that was noticed by mission controllers monitoring telemetry data was not seen until Orbiter re-entry,

Prior and current IMS applications

*Hybrid Combustion Facility Fuel Flow Monitoring
*UH-60 Helicopter Engine Monitoring
*ISS Beta Gimbal Unit
*Stratospheric Observatory for Infrared Astronomy (SOFIA) telescope systems (simulation)
*Aircraft Flight Control Surface Failure Situational Awareness (simulation)
*ARC/JPL/DFRC/F/A-18 System Monitoring Demonstration Flight (engine Systems)
*Shuttle Columbia Ascent Analysis
*Shuttle Wing Leading Edge Impact Detection System (WLEIDS)
*Space Shuttle Main Engine
*ISS Control Movement Gyro

Conclusions

Early results from the Inductive Monitoring System show that it is feasible to automatically construct a useful system monitoring knowledge base from archived system data using clustering techniques. These knowledge bases could provide system monitoring capability comparable to that obtained by model based reasoning techniques, without requiring the cost and effort of building system models. In addition, the IMS monitoring routine may be used for real time or near real time system monitoring. As a mission control tool, IMS could help augment controller awareness of vehicle health and provide early detection of possible anomalies. For example, in an analysis of the STS-107 shuttle, IMS revealed evidence of the Thermal Protection System anomaly within minutes of the foam strike while current mission control tools did not detect the problem until Orbiter re-entry, 17 days later. IMS applications currently under development include a turbine aircraft engine monitoring system, and monitors for various subsystems of the Stratospheric Observatory for Infrared Astronomy (SOFIA), an airborne observatory co-developed by NASA and the German space agency DLR. Techniques to assist in parameter selection for IMS vectors, analyze IMS result trends, and integrate IMS monitoring with diagnostic routines are also being studied.

Points of Contact:

David Iverson
NASA Ames - Intelligent Systems Division
David.L.Iverson@nasa.gov

Group Web Page:

dataminng.arc.nasa.gov